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Measuring the Technical Efficiency of Airports in Latin America

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Abstract

This paper studies the technical efficiency of airports in Latin America. The evolution of productive efficiency in the region has seldom been studied, mainly due to lack of publicly available data. Relying on a unique dataset that was obtained through questionnaires distributed to airport operators, the authors use Data Envelopment Analysis methods to compute an efficient production frontier and compare the technical efficiency of Latin American airports relative to airports around the world. In a second stage, they estimate a truncated regression to study the drivers of observed differences in airport efficiency. According to the results, institutional variables (private/public operation), the socioeconomic environment (level of gross domestic product), and airport characteristics (hub airport, share of commercial revenues) matter in explaining airport productive efficiency. Finally, the authors compute total factor productivity changes for Latin American airports for 1995–2007. The region has implemented a wide variety of private sector participation schemes for the operation of airports since the mid 1990s. The results show that private operators have not had higher rates of total factor productivity change.

This paper—a product of the Sustainable Development Department, Latin America and the Caribbean Region—is part of a larger effort in the department to understand the determinants of performance in the infrastructure sectors. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at tserebrisky@worldbank.org and sergio.perelman@ulg.ac.be.

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1. Introduction

During the last two decades there has been a growing interest in measuring the efficiency and performance of airports. On one hand, the process of introducing private participation in the management and operation of airports and the birth of regulatory agencies in charge of setting tariffs for the sector brought along the need to assess the way in which airports are being operated. On the other hand, with the liberalization of competition among airlines, airports started competing with each other for connecting traffic (to become hub airports) which prompted them to increase their efficiency.

This interest has spurred a growing literature aimed at estimating the efficiency of the airport sector, mainly through the use of data envelopment analysis (DEA) methods. To the best extent of our knowledge, there has not been any study that computes the efficiency and performance of a representative sample of airports in Latin America. This region has implemented a wide variety of private sector participation schemes including concessions of several groups of airports (Mexico), a single concession of a group of airports with more than 90 percent of the air transport market (Argentina), single airport concessions (Chile), and a combination of single and group airport concessions (Peru). Several hypotheses can be provided to explain why airport efficiency in Latin America has not been the subject of academic research but the most likely reason is the lack of publicly available data.

The main objective of this paper is to fill this gap in the literature. We are able to do so using data collected from a questionnaire that was sent, as part of a World Bank study on airports, to the major airport operators in LAC (see Table A1 in the Appendix for a list of airports that responded to the questionnaire). It should be noted that the sample assembled for this study is representative of the air transport sector in the LAC region. Indeed, the airports included in the sample account for more than 80% of total passengers and aircraft movements in the region and for 70% of total air cargo.

The paper first computes a data envelopment analysis (DEA) activity frontier for commercial airports around the world, using the data collected through the questionnaire together with information from airports in Europe, North America and Asia-Pacific taken from the Airport Benchmarking Report elaborated by the Air Transport Research Society (ATRS). These estimations allow us to observe where LAC airports stand relative to the best practices in the sector. The method used also allows us to identify the peers of each airport in Latin America (i.e. airports around the world which are comparable to LAC airports and which operate on the efficiency frontier).

We then proceed to identify factors that drive the observed differences in technical efficiency in the airport sector. In order to do this we estimate a truncated regression model using the efficiency scores of the DEA activity frontier as the dependent variable, and as independent variables several factors that attempt to capture the institutional framework and socioeconomic environment in which airports operate as well as other airport specific characteristics.

Finally, the dataset we use in this paper also allows us to measure Total Factor Productivity Changes (TFPC) for LAC airports over the period 1995-2007. The methodology used to perform these estimations consists on the computation of a Malmquist quantity index of TFPC based on the non-parametric DEA approach.

The rest of the paper is organized as follows. Section 2 presents a brief review of the existing related literature. In Section 3 we present our estimations of a DEA activity frontier for commercial airports around the world and use these results to identify the peers of each of the airports in LAC. Section 4 studies the determinants of airport efficiency by estimating a truncated regression model. Section 5 presents Malmquist quantity indexes of TFPC for LAC airports over the period 1995-2007. Finally, Section 6 presents some concluding remarks.

2. Literature Review

Guillen and Lall (1997) pioneered the use of Data Envelopment Analysis techniques to study efficiency in the airport sector. Their paper uses data from 21 US airports for the period 1989-1993. Using this dataset they define airports as producing two different classes of services – terminal services and movements – and then proceed to compute two different DEA frontiers, one for each of these two services. Finally, using Tobit regressions, they estimate the effect that different variables (like whether or not an airport has rotational runways, preferential runway use or existence of airport operational constraints) have on the efficiency scores of each airport.

Following Guillen and Lall (1997), a literature flourished using DEA methods to study the technical efficiency of the airport sector. In what follows we do not attempt to provide a complete account of this literature. Instead, we review the set of existing papers that is the most relevant for our paper. For a more complete and comprehensive account we refer the reader to Pestana Barros and Dieke (2008) [2].

Using a Malmquist total factor productivity index and data envelopment analysis, Abbot and Wu (2002) investigate the efficiency and productivity of Australian airports during the 1990s. Their results show that Australian airports recorded strong growth in technological change and total factor productivity during this period. However, this growth was based almost exclusively on a shift of the production frontier, with growth in technical and scale efficiency lagging behind.

Pestana, Barros, and Dieke (2008) compute a single DEA frontier for Italian airports using data from the period 2001-2003. However, instead of using a Tobit regression to find determinants of airport efficiency as in Gillen and Lall (1997), following the suggestions made by Simar and Wilson (2007), they estimate a truncated regression. Among many other results, Pestana, Barros, and Dieke (2008) find that Hub airports tend to be more efficient and that privately operated airports also tend to have higher efficiency scores than their publicly operated counterparts. Following Pestana, Barros, and Dieke (2008) and Simar and Wilson (2007), in this paper we also rely on truncated regressions to study the determinants of the observed differences in airport efficiency.

It is worth highlighting that there are a few papers that study the efficiency of airports in Latin America. For example, Flor and de la Torre (2008) use DEA methods to analyze efficiency and total factor productivity of airports in Peru. Similarly, Fernandes and Pacheco (2002) employ DEA methods to compute a production frontier using data for Brazilian airports and Gomez

[2] Some other examples not mentioned in the main text are Gillen and Lall (2001), Murillo-Melchor (1999) and Fung *et al* (2008).

Lobo and Gonzalez (2008) also employ DEA to compare only one airport in LAC (Benito Merino airport in Santiago de Chile) with a set of airports in other regions. However, these papers focus on the efficiency of the airport sector in one single Latin American country. Indeed, to the best extent of our knowledge, this paper is the first that computes a global efficient frontier for the airport sector including data from a representative set of Latin American countries. In contrast to previous studies, this paper identifies how far away Latin American airports stand from the best practice worldwide.

Given the trend towards the introduction of private sector participation in the airport sector, one of the variables we are interested in testing is the effect that ownership has on airport efficiency. There are other papers that study this issue. For example, using DEA methods Parker (1999) analyses the effect that privatization had on the efficiency level of British airports and finds that privatization had no noticeable impact on technical efficiency. Based on panel data for the major airports in Asia-Pacific, Europe and North America for the years 2001-2003, Oum, Adler and Yu (2006) study the effect that the type of ownership has on productive efficiency and profitability. Their results suggest that airports with government majority ownership and those owned by multi-level government are significantly less efficient than airports operating under private majority ownership.

Lastly, it should be noted that DEA is not the only methodology available that can be used to study the efficiency of the airport sector.[3] Indeed, some authors have studied productivity in this sector through methods different than DEA. For instance, Hooper and Hensher (1997) use index number methods to study the evolution of total factor productivity of Australian airports for the period 1988-1992. Oum, Yan and Yu (2008) study the effects of ownership types on airports' cost efficiency by applying stochastic frontier analysis to a panel data of the world's major airports. Pestana Barros (2008) also uses stochastic frontier analysis to study the technical efficiency of airports in the UK. Finally, analyzing the efficiency of European airports, Pels, Nijkamp and Rietveld (2001) compare the results they get from DEA methods to the results obtained using stochastic frontier analysis. Their analysis shows that the stochastic frontier model they consider reproduces the DEA results in quite a reasonable way.

3. Computing a Technical Efficiency Frontier for Airports around the World

In this section we compute a DEA activity frontier for commercial airports around the world. We use data for the years 2005 and 2006 from 22 LAC airports, in addition to 23 airports from Asia-Pacific, 40 from Europe and 63 from Canada and the US (see Tables A1 and A2 in the Appendix for details of airports included in the sample and the results for non Latin American airports).

DEA is a deterministic non parametric approach used to build a benchmark, best practice frontier, based on available information. The method was first developed by Farrel (1957) and later consolidated by Charnes *et al* (1978). One of the main advantages of this approach is that it takes into account the multi-output multi-input dimensionality of production. Another advantage is that computations are based exclusively on measures of physical outputs and inputs, without

[3] For a complete and updated presentation of frontier analysis methods proposed in the literature, see Coelli et al. (2005) and Fried, Lovell and Schmit (2008).

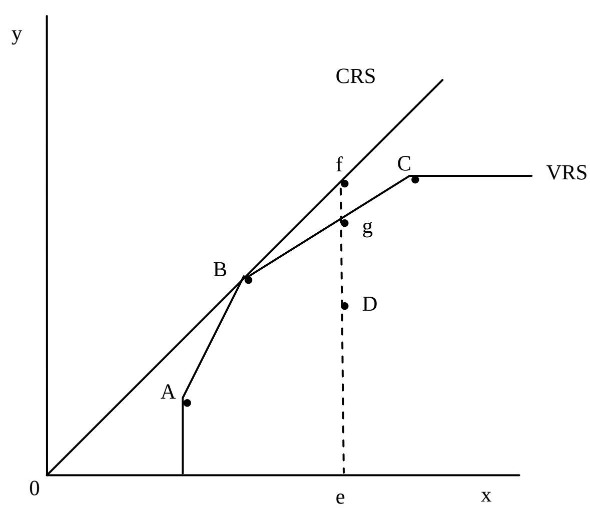
the need of using prices, which are neither available nor are comparable, mainly at the international level.

Two models are computed under the competing assumptions of constant returns to scale (CRS) and variable returns to scale (VRS). This allows us to compute scale efficiencies and to identify for each airport the returns to scale region - increasing, constant or decreasing - in which it operates. We assume that airports have as production target the maximization of outputs for a given input combination; therefore, we use an output oriented framework.

Figure 1 illustrates DEA computations in a simple two-dimensional output (y) input (x) setting. A, B, C and D represent the observed units of production (e.g. airports). Using the available information two frontiers are drawn assuming either constant returns to scale (CRS) or variable returns to scale (CRS). The outcome is: firm B is technical efficient under both assumptions, VRS and CRS technologies; units A and C are technical efficient only when variable returns to scale (increasing, constant and decreasing) is allowed; and firm D is in both cases inefficient. The vertical projection of firm D on the VRS and CRS frontiers (vectors *g* and *f* respectively) indicate the potential, best-practice, output of unit D compared with its peers: unit B under CRS and units B and C under VRS.[4]

Continuing with unit D as an example in Figure 1,VRS technical efficiency (TE-VRS) corresponds to the ratio *eD/eg*, CRS technical efficiency (TE-CRS) to the ratio *eD/ef*, and the ratio between them, *eg/ef*, the potential technical efficiency gain associated with the scale of operation (scale efficiency, noted SE) . The distance *fg* indicates the loss of production of unit D due to decreasing returns (DRS). It should be noted that unit C is also penalized for operating at a large scale while, on the contrary, unit A is penalized because it is operating at a (sub-optimal) increasing returns scale (IRS). Only unit B operates at the optimal scale in this example.

Figure 1: DEA frontier illustration



[4] The linear programs (LP) used to compute TE-VRS and TE-CRS are presented in the methodological section of the Appendix.

Frontier models like DEA require the specification of inputs and outputs used in the industry under study. There have been considerable differences in the literature of airport efficiency estimation at the time of defining inputs and outputs. On the output side the more complete and often used model specification includes three output dimensions: passenger, freight and aircraft movements. On the inputs side there is fewer consensuses in the literature, mainly due to data availability problems. In any case, most studies include a bundle of variables representing labor and capital inputs. The most frequently used variables are the number of employees as proxy for labor input and capital proxies such as the number or size of runways, terminal size and the number of boarding bridges. When comparable accounting data is available, inputs are represented by operating costs and the monetary value of the capital stock.

In our case, and given the data at our disposal, we chose to specify a three-input three-output production function. The outputs that we use are (i) number of passengers, (ii) tons of freight and (iii) number of aircraft movements while the inputs are: (i) number of employees, (ii) number of runways and (iii) number of boarding bridges.

The dataset is well balanced for the 22 LAC airports but unbalanced for the other regions of the world, particularly for European airports. For this reason, we chose to pool and computed a single DEA frontier for the period 2005-2006.

Table 1 presents descriptive statistics on outputs and inputs by region. LAC airports are on average smaller than those from the other regions in terms of all three outputs: passenger, tons and aircraft movements. However, in spite of these differences in the scale of production, on average LAC airports employ nearly as much staff as Canadian and US airports[5]. At the same time, in terms of capital investments, the number of runways and boarding bridges is several times lower in LAC airports than in Canadian and US airports.

[5] The observed difference in employees does not directly imply there is over employment in LAC airports. The difference could be the result of different approaches to outsourcing airport services.

Table 1: Descriptive statistics by world region (2005-2006)

Stat.	Outputs (x1000)			Inputs		
	Passenger	Tons of freight	Aircraft movements	Employees	Runways	Boarding bridges
LAC (22 airports, 44 observations)						
Mean	6,430.6	117.2	96.1	424.0	1.5	11.3
STD	6,033.6	119.0	82.9	412.0	0.5	9.7
Min.	181.0	0.2	1.9	20.0	1.0	0.0
Max.	24,727.0	470.9	356.0	1,568.0	2.0	38.0
ASIA (23 airports, 39 observations)						
Mean	18,776.7	836.0	148.2	1,044.0	1.7	52.3
STD	12,432.4	970.7	82.7	1,107.3	0.6	35.5
Min.	1,293.3	10.3	10.5	137.0	1.0	0.0
Max.	45,100.0	3,600.0	286.5	4,873.0	3.0	143.0
Europe (40 airports, 66 observations)						
Mean	19,305.0	318.3	211.8	2,029.4	2.3	67.9
STD	15,728.4	515.7	127.8	2,982.6	1.0	58.3
Min.	1,218.9	3.6	29.8	298.0	1.0	6.0
Max.	67,915.0	2,131.0	533.0	17,528.0	6.0	264.0
Canada & US (63 airports, 125 observations)						
Mean	21,318.4	406.5	310.9	549.9	3.4	69.9
STD	17,976.6	641.8	196.7	480.7	1.2	42.6
Min.	2,657.1	3.6	60.5	119.0	1.0	14.0
Max.	85,907.4	3,713.4	980.4	3,000.0	7.0	178.0

The computed Technical Efficiency (TE) scores for airports in the four regions are presented in Table 2.[6] The average TE score of airports in all regions is 0.545 under the constant returns to scale (CRS) assumption. This means that, on average, the airports included in the sample are half technically efficient or, in other words, that they could almost double their outputs using the same quantity of inputs.

However, part of the distance to the best practice CRS frontier is explained by the scale of operation. Under the variable returns to scale (VRS) assumption the average TE is 0.629. Therefore the average scale efficiency (SE) is 0.875. Moreover, for each scale inefficient airport it is possible to identify the type of scale inefficiency: either increasing or decreasing returns to scale, denoted in Table 2 as IRS and DRS, respectively. In the last three columns of Table 2 we report the percentage of airports corresponding to this classification. Grouping all regions,

[6] All DEA computations, including Malmquist indexes presented in Section 5, were performed using the DEAP program developed by Coelli (1996).

44.5%, 8.4% and 47.1% of the airports in our dataset operate under increasing, constant and decreasing returns to scale, respectively.[7]

LAC airports appear to be the ones that suffer the most from a suboptimal scale operation. Scale inefficiency is close to 20% (SE = 0.801), mainly concentrated in the increasing returns to scale area (70.5% of observations). This means that on average, airports in LAC could improve their efficiency 20% if they were to increase its scale of operation to the optimal scale. On the contrary, nearly 70% of Canadian and US airports operate in the decreasing returns to scale region. The results of return to scale diagnosis coincided with the intuition: airports in LAC are smaller and given that the production technology of airports is characterized by large fixed investments (runways, terminals) it is logical to expect that smaller airports are still in the increasing return to scale zone of the production function[8].

As is the case whenever international comparisons among airports are made, in particular when efficiency is compared, care must be exercised when interpreting the results (UK Civil Aviation Authority, 2000). Airports operate under very different environments and subject to different sets of regulations. For instance, European airports tend to employ more personnel than US airports as the later usually lease terminals to airlines. Difference in the operational approaches followed by airports could influence the results. These differences are well explained in ATRS' reports which are the most widely used data source for international airport comparisons, and the one used in this paper.

Table 2: Average TE scores and scale efficiency by region (2005-2006 average)

World Region	**Technical efficiency**			**Returns to scale diagnosis** (% of observations)		
	TE-CRS	**TE-VRS**	**SE**	**IRS**	**CRS**	**DRS**
Latin America	0.532	0.690	0.801	70.5	9.1	20.5
Asia	0.670	0.771	0.869	84.6	12.8	2.6
Europe	0.490	0.530	0.927	43.9	6.1	50.0
Canada & US	0.540	0.616	0.875	23.2	8.0	68.8
All	0.545	0.629	0.875	44.5	8.4	47.1

Table A3 in the Appendix replicates Table 2 but adds the results of computing average TE scores using a model with two inputs (leaving runways and staff and taking out boarding bridges). Investment in boarding bridges show a significant underinvestment in LAC (569,000

[7] The results presented here were confirmed using the bootstrapping method proposed by Simar and Wilson (1998) and the FEAR software developed by Wilson (2007). The Spearman correlation between DEA TE scores computed with the original sample and those computed using the data generated by a smooth bootstrap re-sampling (400 replications) procedure were in all cases higher than 0.90.

[8] Airports identified as operating at the optimal scale (CRS) in our database handle between 20 to 30 millions of passenger each year. This result differs from previous estimations that found that the segment of constant returns to scale starts around the 3 million mark (Doganis, 1993).

passengers per boarding bridge, compared with 359,000, 284,000 and 305,000 in Asia, Europe and North America respectively) and given that robust and comparable information on quality is not available, with the specification of inputs and outputs chosen in this paper, DEA tends to reward airports that underinvest in capital. When taking out boarding bridges the average TE score for LAC airports fall significantly relative to the average in other regions.

Table 3 presents detailed results for LAC airports. Only two airports in the region are technically efficient under both CRS and VRS: CGH (Aeroporto de São Paulo /Congonhas) and VCP (Aeroporte Internacional de Viracopos-Campina). However, it is important to highlight that VCP is a special case: it is an efficient unit in DEA 'by default', which occurs when a production unit has no peers to which it can be compared. VCP is an airport that can be characterized as a dedicated freight airport as it has virtually no passenger movement and no boarding bridges. Other results of Table 3 can be summarized as: (a) TE scores for LAC airports show notable variations: from airports on the frontier (with a value of 1) to airports that have TE scores close to 0; and (b) If the scale of operation is out of the control of airports managers, as we suspect, the most important information correspond to the TE-VRS results. In this case the TE of LAC airports improve. Out of 22 airports, 6 are on the frontier. The subsection of sources of technical efficiency tries to identify the variables that explain the observed differences in TE scores across airports.

Table 3: Technical efficiency and scale efficiency scores (2005-2006 average)

Country	Airport	TE-CRS	TE-VRS	SE
Argentina	**AEP**	0.612	0.998	0.614
	EZE	0.414	0.417	0.993
	FTE	0.115	1.000	0.115
Brazil	**BSB**	0.498	0.536	0.931
	CGH	1.000	1.000	1.000
	GIG	0.318	0.320	0.994
	GRU	0.677	0.678	0.998
	MAO	0.377	0.692	0.544
	VCP	1.000	1.000	1.000
Chile	**SCL**	0.786	1.000	0.786
Colombia	**BAQ**	0.329	0.524	0.628
	CLO	0.496	0.734	0.676
Costa Rica	**SJO**	0.594	0.983	0.605
Ecuador	**GYE**	0.472	0.646	0.739
El Salvador	**SAL**	0.114	0.127	0.900
Mexico	**CUN**	0.860	1.000	0.860
	GDL	0.643	0.649	0.991
	MEX	0.961	0.963	0.998
	MTY	0.403	0.410	0.982
Panama	**PTY**	0.164	0.178	0.926
Peru	**LIM**	0.621	0.961	0.646
Dominican Rep.	**SDQ**	0.260	0.372	0.699
ALL		0.532	0.690	0.801

The use of DEA allows the identification of peers for each airport, which are the set of efficient airports that make up the relevant frontier for a given airport. Table 4 presents the peers for LAC airports in 2005 under the VRS model. Observations for peers corresponding to 2006 are in brackets and airport peers from the LAC region appear underlined. It should be noted that, by construction, technically efficient airports do not have other airport as peers. Technical inefficient airports have, on the contrary, a benchmark composed by other units. Given the 3-output 3-inputs dimensionality of the production setting, the maximum number of peers is 6 but an airport can have less than 6 peers.

It is important to remark that some LAC airports are peers for other airports. Not only do they serve as peers (benchmark) for other airports in the LAC region but also for other airports around the world. This is the case mainly of CGH, which is a reference for 28 observations (2005 and 2006 airport observations taken together). Other airports playing the same role of peers are AEP (Aeroparque Jorge Newbery, Buenos Aires), SCL (Comodoro Merino Benítez, Santiago de Chile), CUN (Cancún) and, to a less extent, FTE (Aeropuerto Internacional de El Calafate) and SJO (Aeropuerto Internacional Juan Santamaria, San José, Costa Rica). An interesting result is that all LAC airports in our sample, with the exception of MAO (Aeroporto Internacional Eduardo Gomes, Manaus), have as peers at least one Latin American airport. Eight airports from outside the LAC region act as peers for LAC airports: XMN (Xaimen), ICN (Seoul), SDF (Louisville), LAX (Los Angeles), MEM (Memphis), SNA (Costa Mesa, California), ATL (Atlanta) and MFM (Macau).

For illustration purposes, let us look in more detail at one observation, the case of BSB (Aeroporto Internacional Juscelino Kubitschek, Brasilia). For this airport we computed a TE-VRS score of 0.552, which corresponds to a 45% output inefficiency diagnosis. The airports identified as peers for BSB are CGH and three US airports: MEM (Memphis), LAX (Los Angeles) and SNA (Costa Mesa, California). If we simply compare BSB against CGH, its only LAC peer, and look at some of their main output-input features (for the year 2005), we get a confirmation of the DEA result. On the output side BSB handles 9.4 million passengers per year, against the 17.1 million passengers of CGH. Similarly, BSB had 171.6 thousand aircraft movements in 2005, against 282.6 thousand aircraft movements in CGH. Finally, on the input side we see that BSB had 365 employees and 13 boarding bridges, while CGH had 225 employees and 8 boarding bridges.

Table 4: Peer analysis, DEA-VRS 2005

Country	Airport	TE-VRS 2005	As peer for other airports	Peers				
				1	2	3	4	5
Argentina	AEP	1.000	9	AEP				
	EZE	0.404	0	CGH	(CGH)	(XMN)	(ICN)	(SDF)
	FTE	1.000	7	FTE				
Brazil	BSB	0.552	0	CGH	LAX	MEM	SNA	
	CGH	1.000	28	CGH				
	GIG	0.316	0	(CGH)	(XMN)	(ICN)	ATL	
	GRU	0.680	0	(CGH)	(XMN)	(ICN)	ATL	
	MAO	0.680	0	SJO	(XMN)	MFM	SNA	
	VCP	1.000	0	VCP				
Chile	SCL	1.000	10	SCL				
Colombia	BAQ	0.507	0	FTE	SJO	(XMN)	SNA	
	CLO	0.747	0	(FTE)	SCL	S NA		
Costa Rica	SJO	1.000	6	SJO				
Ecuador	GYE	0.814	0	(FTE)	SJO	(XMN)	SNA	
El Salvador	SAL	0.131	0	(CGH)	LAX	MEM	SNA	
Mexico	CUN	1.000	11	CUN				
	GDL	0.615	0	CGH	FTE	(XMN)	(SDF)	
	MEX	0.947	0	CGH	ICN	(XMN)	ATL	SNA
	MTY	0.424	0	CGH	(FTE)	(ATL)	MEM	SNA
Panama	PTY	0.188	0	CGH	ICN	(XMN)	(SDF)	SNA
Peru	LIM	0.922	0	AEP	(LIM)	(SCL)	(XMN)	SNA
Dominican Rep.	SDQ	0.386	0	AEP	(LIM)	(SCL)	SNA	(XMN)

Notes: Underlined peers are LAC airports. Between brackets are 2006 observations. Other airports: ICN (Seoul, Korea); MFM (Macau); XMN (Xiamen, China); ATL (Atlanta International); SDF (Louisville), MEM (Memphis), LAX (Los Angeles); SNA (Costa Mesa, California).

4. Sources of Technical Efficiency

In this section we estimate the effect that institutional factors, socioeconomic conditions, the demographic environment and characteristics particular to each airport have on **technical** efficiency. We do this by estimating a truncated regression model, using the airport efficiency scores of the previous section as dependent variables and these factors as explanatory variables. The choice of a truncated model is dictated by the nature of the technical efficiency measure (which is by definition truncated at 1.0) and by the findings of the recent academic literature (Simar and Wilson (2007)).[9]

Before presenting our results we stress that service quality is likely to be another potential factor behind the observed differences in airport efficiency. It is likely that, other things equal, airports operating with a large staff and/or a large number of boarding bridges provide better service quality to passengers. Unfortunately, survey data on users' satisfaction is not yet available at an international scale for us to be able to include quality indicators in our regression analysis.

Table 5 presents average values by region for the candidate variables to account for observed differences in technical efficiency. Starting with the institutional setting, Table 5 shows that on average LAC airports operate under a more liberalized framework. Indeed, more than half of LAC airports (54.5%) in our sample operate as private concessions, and 31.8% are regulated by an independent regulatory agency. In contrast, only 25.6% of Asian airports and 37.9% of European airports are under private management, while 10.3% and 16.7% of Asian and European airports respectively are regulated by an independent regulatory agency. Finally, all airports in Canada and the United States are operated by state-owned enterprises, and regulatory agencies in these two countries still depend directly from a political authority (a ministry).

Another potential factor that could have a role in the explanation of airport performance is the socioeconomic environment in which they operate. We incorporate this effect with two indicators: GDP per capita (measured in current dollars) and tourism expenditures (also measured in current dollars). However, it is worth stressing that these variables are only available at the country level and don't correspond necessarily to the area of influence of the airports.[10]

The demographic environment is represented by the concentration of population in the area served by the airport. On average, LAC airports appear to serve very large urban agglomerations, like their Asian counterparts. Compared to European and North-American airports, which are on average located in cities with 3 to 4 million inhabitants, LAC airports are on average located in cities with 8 million people. In the regression analysis this information will be incorporated with a binary (dummy) variable that takes a value 1 for airports located in cities with more than 5 million people and 0 otherwise[11].

Finally, we introduce a set of variables that represent characteristics that are particular to each airport. One of them is their specialization as a hub, represented by the percentage of connecting passengers. LAC airports have the lowest percentage of connecting passengers (and also have the lowest percentage of hubs), followed by Asian airports. The highest percentage is observed among European airports, where nearly one-third of passengers are connecting. Another variable that is particular to each airport is the share of aeronautical revenues in total revenues. In Table 5 below we see that aeronautical revenues are on average rather more

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[9] We estimate truncated regressions using the "truncreg" procedure of SATA 9.0.

[10] Given that our dataset contains several airports in the United States and given the availability of data, for these airports we used GDP per capita of the state in which each airport is located instead of GDP per capita for the country as a whole.

[11] The value of 5 million corresponds to the mean of the population of the cities where airports are located.

important for LAC airports (where they represent almost 60% of total revenues) than for airports in any other region.

Table 5: Potential explanatory factors of technical inefficiency (2005-2006)

Explanatory factors	Latin America	Asia	Europe	Canada & United States
Institutional framework				
Private airport (%)	54.5	25.6	37.9	0
Independent Regulatory Agency (%)	31.8	10.3	16.7	0
Socioeconomic environment				
GDP per capita (U$D)	5,442	17,397	32,598	42,219
Tourism expenditures per capita (U$D)	69	532	943	393
Population concentration				
Population in the area (1,000)	7,719	6,709	3,200	3,984
Population > 5,000,000 (%)	45.5	48.7	22.7	34.4
Airport characteristics				
Hub airport (%)	9.1	17.9	40.9	27.2
Passengers connecting (% of passenger)	7.9	9.5	32.8	23.4
Aeronautical Revenues (% of total revenue)	56.9	53.8	51.6	49.2

Source: Institutional and Airport characteristics variables were constructed with information from Air Transport Research Society's Benchmarking reports. Socioeconomic and population variables were obtained from World Bank's World Development Indicators database.

Table 6 reports the results – in the form of marginal effects – of estimations for alternative truncated regression models. The first two columns show the estimates of two models with TE-VRS scores as dependent variable, with and without dummies for each world region. The third column presents the estimates of a model with TE-CRS scores as dependent variable, without regional dummies. The Likelihood Ratio Tests (LT) indicate that in all three cases the variables included in the model, taken together, have a statistically significant effect on the dependent variable.

First, it should be noted that there are two variables that appear as the main drivers of technical efficiency in the airport sector. On the one hand hub airports are, on average and depending on the specification of the model, 10% to 15% more efficient than non-hub airports. On the other hand, the size of the population in the area served by the airport also seems to matter: airports located in cities with more than 5 million inhabitants are 17% to 20% more efficient than airports that serve less populated areas.

Second, our results show that the institutional variables (whether the airport is private or public and whether it is regulated by an independent regulatory agency), are associated with positive marginal effects. However, these variables are not statistically significant, with the exception of the dummy for private airports under the VRS assumption. According to these results, privately operated airports tend to be more efficient, with a TE score that is on average 6% to 8% points higher than publicly operated airports.

Another important feature that distinguishes airports is the importance of aeronautical activities in their operation. As expected, the importance of these activities, summarized by the share of aeronautical revenues in the total airport revenue, plays a negative effect on efficiency (although this effect is statistically significant only when we use TE-VRS scores as the dependent variable). In other words, airports in which non-aeronautical (i.e. commercial) activities are more important tend to be more efficient. The estimated marginal effect indicates that, on average and holding the other variables constant, a 10% increase in the share of aeronautical revenues appears to be related with a loss in technical efficiency of nearly 2%.

GDP per capita seems to have a positive effect on airport efficiency. However, **its** estimate is only significant in the VRS model (with regional dummies). In this case, when GDP per capita increases 10,000 USD higher the technical efficiency of airports is expected to increase 6%. Finally, tourism expenditure is not significant in the three specifications.

Table 6: Truncated regressions - Marginal effects

Explanatory factors	**TE-VRS With regional dummies**		**TE-VRS Without regional dummies**		**TE-CRS Without regional dummies**	
	Marginal effect	**(std)**	**Marginal effect**	**(std)**	**Marginal effect**	**(std)**
Institutional framework						
Private airport (dummy)	0.064	(0.036)*	0.082	(0.035)**	0.068	(0.041)
Regulation authority (dummy)	0.048	(0.048)	0.041	(0.050)	0.083	(0.059)
Socioeconomic environment						
GDP per capita	0.006	(0.002)***	0.001	(0.001)	0.001	(0.001)
Tourism expenditures per capita	- 0.033	(0.049)	- 0.005	(0.033)	- 0.045	(0.036)
Population concentration						
Population > 5,000,000 (dummy)	0.169	(0.025)***	0.201	(0.027)***	0.173	(0.031)***
Airport characteristics						
Hub airport (dummy)	0.122	(0.028)***	0.099	(0.031)***	0.153	(0.031)***
Aeronautical Revenues	- 0.150	(0.081)*	- 0.183	(0.085)**	- 0.134	(0.102)
Control variables (dummies)						
Asia	0.059	(0.047)	-	-	-	-
Europe	- 0.200	(0.059)***	-	-	-	-
Canada and US	- 0.201	(0.069)***	-	-	-	-
Year 2006	- 0.023	(0.023)	- 0.107	(0.024)	- 0.210	(0.274)
LR test	$Chi^2(11)$	110.3***	$Chi^2(8)$	80.8***	$Chi^2(8)$	56.7***
Observations	251		251		251	

***, **, and *: Below the 1%, 5% and 10% statistical significance thresholds, respectively.

5. Measuring Productivity Change of LAC Airports

The objective of this section is to assess how airport productivity evolved in Latin America. To that end we compute annual total factor productivity change (TFPC) for LAC airports over the period 1995 to 2007. The period covered was determined by the data compiled through the questionnaires distributed for the elaboration of a World Bank report on Airports in Latin America (World Bank, 2009). We rely on the same 3-output 3-input model specification used in the calculation of technical efficiency scores of section 3 and the methodology consists in the computation of a Malmquist quantity index of TFPC based on the non-parametric DEA approach.

Figure 2 illustrates the computation of the Malmquist index in a simple one-output (y) one-input (x) setting. Assuming constant returns to scale, the best practice technologies for period *s* and period *t* are defined by the period *s* and *t* DEA frontiers, respectively. The quantities of input and output of a particular unit in periods *s* and *t* are defined by points (y_s, x_s) and (y_t, x_t), respectively. Thus the distance of the unit in period *t* relative to the period *t* frontier is equal to y_t / y_d and the distance in period *s* relative to the period *t* frontier is equal to y_s / y_b. Using this information and the distances computed relative to the period *t* frontier, y_t / y_c and y_s / y_a the Malmquist index is computed as follows: $\left[\frac{y_t / y_d}{y_s / y_b} . \frac{y_t / y_c}{y_s / y_a}\right]^{0.5}$.

The Malmquist index of TFPC presents two advantages with respect to traditional index numbers. On the one hand prices are not needed to calculate this index. On the other hand, the index can be decomposed into a measure of technical progress (TC) of the activity level taken as a whole, and another measure (TEC) that captures how each unit is catching up with respect to the technological frontier. Its main disadvantage compared with traditional index numbers is that it cannot be computed separately for each unit. Its computation relies on the estimation of sequential frontiers. Thus, panel data must be available for benchmarking purposes.[12]

[12] The reader is referred to Färe *et al* (1994) for details on the methodology, including its decomposition.

Figure 2: The Malmquist index of productivity change

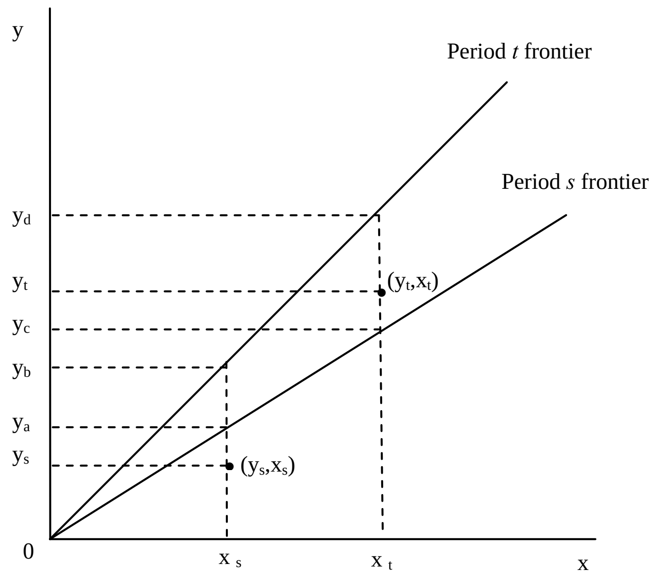

Table 7 presents descriptive statistics for the three sub periods in which we decomposed the sample: 1995-1999, 2000-2003 and 2004-2007. For each of these three sub periods the number of airports in our sample varies noticeably, from 7 to 22.[13] As a consequence, the benchmark used for TFPC computations varies as well.[14]

The average TFPC values reported in Table 8 exclude 14 over 154 observations. These observations correspond to airports which introduced major changes in their capital stock in a particular year (given by increases in either the number of runways or boarding bridges). Given that these types of investments are lumpy by nature and that their introduction is followed by an initial period of underutilization, they tend to have a big negative impact on measures of productivity change. Table A4 in the Appendix reports the results for all airports and years. Those cases corresponding to changes in the stock of either the number of runways or boarding bridges are in bold. As expected, the TFPC index corresponding to these observations are highly negative.

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[13] The only criterion used to split the data was to obtain 3 sub periods with equivalent number of years. The sample covers a large range of airports sizes. Measuring size by the number of passengers per year the sample ranges from 158,000 to 25,800,000 passengers. Zero values are reported for some variables. On the output side, this is the case for freight transportation for at least one airport. And on the input side, at least one airport is not equipped with boarding bridges, still in the year 2007.

[14] Due to the unbalanced nature of our dataset we did not decomposed the TFPC results presented in Table 8.

Table 7: Descriptive statistics by period

Stat.	Outputs (x1000)			Inputs		
	Passenger	Tons of freight	Aircraft movements	Employees	Runways	Boarding bridges
1996-1999 (7 airports, 26 observations)						
Mean	5,039.7	145.4	119.1	723.5	1.5	9.7
STD	4,586.1	125.7	80.9	690.0	0.5	10.1
Min.	250.6	21.4	30.5	77.0	1.0	0.0
Max.	14,705.1	409.2	293.8	2,056.0	2.0	38.0
2000-2003 (17 airports, 60 observations)						
Mean	6,136.6	132.8	112.4	429.3	1.5	11.8
STD	5,314.4	124.2	88.0	465.8	0.5	10.9
Min.	654.8	10.4	29.5	56.0	1.0	0.0
Max.	21,694.0	418.9	334.5	1,940.0	2.0	38.0
2004-2007 (22 airports, 85 observations)						
Mean	6,579.4	121.1	99.1	433.9	1.5	12.0
STD	5,992.7	120.6	83.6	421.9	0.5	10.7
Min.	157.9	0.0	1.9	20.0	1.0	0.0
Max.	25,882.0	470.9	379.0	1,598.0	2.0	56.0

In Table 8 we present the main results: TFPC by sub period and by airport. In order to avoid potential biases due to unbalanced panel data, Malmquist index computations were performed separately for each two-year sequential period using in each case a balanced panel of airlines.

Average productivity growth oscillated over the three sub periods. Between 1995 and 1999, airports in the region posted an average annual productivity growth of -2.7%. However, it should be noted that limited data is available for this period and consequently the result is biased by the high negative value of the airport in Barranquilla, Colombia. Airports in Brazil show an increase, on average of 5.4%. Average productivity growth during the intermediate period (1999-2003) was negative (-1.2% per year), and was driven mainly by some airports which experimented dramatic losses in productivity, like EZE (Aeropuerto Internacional Ministro Pistarini, Buenos Aires) which showed an average loss in productivity of -18.1% per year over this period as a direct consequence of the severe economic and financial crisis Argentina suffered during 2001/2002. On the contrary, positive rates of growth appear to be the norm (with only some exceptions) during the last sub period (2003 to 2007). The average TFPC rate was 3.9% during this period, with many airports experimenting annual productivity growth rates close to, or even higher than, 10%.

Table 8: Average TFPC by airport and sub period (Annual %)

Country	Airport	1995-1999	1999-2003	2003-2007
Argentina	AEP	-	-7.0	-3.0
	EZE	-	-18.9	4.0
	FTE	-	-	22.9
Brazil	BSB	10.0	5.4	2.9
	CGH	13.8	2.6	-4.0
	GIG	7.4	-5.5	16.3
	GRU	3.5	-0.9	2.7
	MAO	-2.3	0.3	6.8
	VCP	0.9	-7.6	-0.8
Chile	SCL	-	1.3	2.0
Colombia	BAQ	-23.0	-8.4	1.5
	CLO	-	-6.2	-5.1
Costa Rica	SJO	-	22.1	0.0
Ecuador	GYE	-	-	8.1
El Salvador	SAL	-	2.7	1.4
Mexico	CUN	-	6.6	-0.3
	GDL	-	-6.1	9.5
	MEX	-	1.1	4.9
	MTY	-	5.8	4.7
Panama	PTY	-	-	7.4
Peru	LIM	-	-	9.7
Dominican Rep.	SDQ	-	-	-3.7
ALL		-2.7	- 1.2	3.9

A relevant policy question is whether private operated airports in LAC, a region that has experienced with a wide variety of private sector participation schemes for the operation of airports, have higher productivity gains. Table 9 sheds some light to this question. As the exercise of estimation of explanatory variables of TE scores at the international level showed, private operation is a relevant variable to explain differences in productivity. Table 9 also presents changes in productivity dividing airports by size and then uses the Work Load Unit measure to weight airports to avoid reaching a conclusion on public/private operated airports biased by the size of airports.

The results reported in Table 9 show that the largest airports are the ones that registered faster productivity growth. In particular, those airports that handle between 7.5 and 10.0 million passengers per year posted an average annual growth rate of 5.4% for the whole period, and an even higher growth of 7.0% during the last sub period. Interestingly, the category made up by the three biggest airports in the region (CGH, GRU and MEX, which handle more than 10 million passengers per year), grew faster during the first sub period, but at a rather low rate over the two last sub periods.

Public airports appear to have performed better on average over the whole period compared to private airports (annual productivity changes of 2.9% and 0.7%, respectively). Nevertheless, if we focus on their evolution over the last two sub periods, for which the available information is more complete, both groups behaved quite similarly, registering negative productivity growth during the period 1999-2003 and positive growth between 2003 and 2007 (although with a slightly more favorable profile for public airports). These results are confirmed when we weight TFPC averages using work-load unites (WLU) as the weight variable.[15] Weighted averages give a better approximation of the productivity growth for the whole airport activity in the region. Since larger airports performed better than smaller ones, we see that the weighted average TFPC is higher than the non-weighted average (2.6% against 1.9%).

The results reported in Table 9 were evaluated applying the sensitivity analysis, bootstrapping method, introduced by Simar and Wilson (1999). Using FARE (Wilson, 2007), we compute 10% confidence intervals for each Malmquist TFP change observation in the sample. And using this information we distinguish observations with significant positive TFP change (>1.0), those with upper and lower confidence interval boundaries higher than 1.0, those with significant negative TFP change (<1.0), those having lower and upper boundaries lower than 1.0, and finally observations with no TFP change correspond to cases where the confidence interval includes the value of unity.

In all cases, the result of this sensitivity analysis showed a high correlation with the results presented in Table 9. For instance, among the observations corresponding to LAC public airports 57% and 22% showed, respectively, positive and negative significant TFP changes. While among private airports the shares of positive and negative changes were 43% and 29%, respectively. In the same vein, 73% of positive TFP changes were observed during the 2003 to 2007 period, while 39% during the period 1999 to 2003 and 57% during the first period. Finally, it is among the great size LAC airports that the proportion of positive annual TFP changes was the highest, 63% against 15% of negative changes, while the smallest airports, with less than 5 million passengers, positive and negative changes represented 42% and 34%, respectively.

[15] One WLU is equivalent to one terminal passenger or 100 kg of freight or mail.

Table 9: Average TFPC by airport categories (Annual %)

Airport categories	1995-1999	1999-2003	2003-2007	ALL
Non-weighted				
Size (10^6 passengers)				
< 5.0	- 5.6	- 1.8	3.5	0.4
5.0 to 7.5	-	- 4.3	3.7	0.5
7.5 to 10.0	8.9	1.7	7.0	5.4
> 10.0	8.5	0.9	1.8	3.4
Private-Public				
Private	- 23.0	- 1.6	3.4	0.7
Public	5.3	- 0.8	4.5	2.9
ALL	2.7	- 1.2	3.9	1.9
Weighted *				
Private-Public				
Private	- 23.2	- 0.5	2.7	1.3
Public	6.1	0.2	4.4	3.2
ALL	5.5	0.0	3.7	2.6

* Weighted by WLU.
Public airports: BSB, CGH, GIG, GRU, MAO and VCP (Brasil); SAL (El Salvador); MEX (México); and PTY (Panamá). Private airports: AEP, EZE, FTE (Argentina); SCL (Chile), BAQ and CLO (Colombia); SJO (Costa Rica); GYE (Ecuador); CUN GDL and MTY (México); and LIM (Perú).
Airport size: < 5.0: BAQ, CLO, FTE, GYE, MAO, PTY, SAL, SDQ and SJO; 5.0-7.5: AEP, EZE, GDL, LIM, MTY and SCL; 7.5-10.0: BSB, CUN and GIG; > 10.0: CGH, GRU and MEX.

6. Conclusions

To the best extent of our knowledge, this paper is the first to conduct a comprehensive efficiency calculation of Latin American airports. Our results indicate that technical efficiency in Latin American airports shows notable variations: from airports on the frontier (with a value of 1) to airports that have technical efficiency scores close to 0. When variable returns to scale are assumed (which implies that the scale of operation is out of the control of airport managers, a sensible assumption) of the 22 LAC airports in the sample, 6 are on the frontier. However, when constant returns to scale are considered, only two airports are on the frontier.

On average, Latin American airports are less efficient than Asian and North American airports when constant returns to scale are assumed, but more efficient than European airports. However, when boarding bridges are excluded and not considered as a proxy for capital investments, LAC airports are on average significantly less efficient than those in the other regions included in the study.

Using the DEA efficiency scores, we estimated a truncated regression model in order to find factors that might explain the observed differences in airport efficiency. As expected, the regression analysis shows that hub airports tend to be more efficient. Moreover, airports which are located in cities with more than 5 million inhabitants are also more efficient than airports located in smaller cities. The level of income (GDP) also seems to positively influence productive efficiency. Airports that rely more on revenue sources other than aeronautical tariffs also tend to be more efficient, a finding consistent with the recent literature (ATRS, 2008). Finally, airports which are privately operated tend to stand closer to the efficient frontier than their publicly operated counterparts, although this effect is not significant across all the different specifications of the model we tested.

Probably the most unexpected result is that privately operated airports in Latin America have not outperformed publicly operated airports. Given the wide variety of private participation schemes used by Latin American countries, this result should lead to more detailed and case by case research to assess the effects of private participation on airport performance. In addition, future research should also assess the impact of private sector participation on the financial efficiency of LAC airports as well as on the quality of service they deliver.

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Appendix

Table A1: Airports in Latin American and Caribbean Airports that responded the questionnaire

Country	*Airport Name*	*IATA Code*
Buenos Aires, Argentina	Aeroparque Jorge Newbery	AEP
Buenos Aires, Argentina	Aeropuerto Internacional Ministro Pistarini	EZE
El Calafate, Argentina	Aeropuerto Internacional El Calafate	FTE
Nassau, Bahamas	Lynden Pindling International Airport	NAS
São Paulo, Brazil	Aeroporto de São Paulo /Congonhas	CGH
São Paulo, Brazil	Aeroporto Internacional de Viracopos-Campinas	VCP
São Paulo, Brazil	Aeroporto Internacional de São Paulo/Guarulhos Governador Andre Franco Montoro.	GRU
Brasilia, Brazil	Aeroporto Interncional de Brasilia Presidente Juscelino Kubitschek	BSB
Manaus, Brazil	Aeroporto Internacional Eduardo Gomes	MAO
Rio de Janeiro, Brazil	Aeroporto Internacional de Rio de Janeiro/Galeão Antonio Carlos Jobim	GIG
Santiago de Chile, Chile	Aeropuerto Int. Comodoro Arturo Merino Benítez	SCL
Bogotá, Colombia	Aeropuerto Internacional El Dorado	BOG
Cali, Colombia	Aeropuerto Alfonso Bonilla Aragón	CLO
Barranquilla, Colombia	Aeropuerto Internacional Ernesto Cortissoz	BAQ
Medellín, Colombia	Aeropuerto Internacional José María Córdova	MDE
San José, Costa Rica	Aeropuerto Internacional Juan Santamaría	SJO
Guayaquil, Ecuador	Aeropuerto Internacional José Joaquín de Olmedo	GYE
San Salvador, El Salvador	Aeropuerto Internacional El Salvador	SAL
Ciudad de Guatemala, Guatemala	Aeropuerto Internacional La Aurora	MGGT
Guadalajara, México	Aeropuerto Internacional De Guadalajara	GDL
Monterrey, México	Aeropuerto Int. General Mariano Escobedo	MTY
Ciudad de México, México	Aeropuerto Internacional Benito Juárez	MEX
Cancún, México	Aeropuerto Internacional de Cancún	CUN
Ciudad de Panamá, Panamá	Aeropuerto Internacional de Tocumen	PTY
Lima, Perú	Aeropuerto Internacional Jorge Chávez	LIM
Sto. Domingo, Rep. Dominicana	Aeropuerto Internacional de Las Américas	SDQ
Port of Spain, Trinidad and Tobago	Piarco International Airport	POS

Table A2: Technical efficiency scores for all airports other than Latin American airports included in our sample (data from the ATRS Airport Benchmarking Report)

Airport	*IATA Code*	*CRS*	*VRS*	*Scale Efficiency*
Auckland, New Zealand	AKL	0.648	0.879	0.737
Bangkok, Thailand	BKK	0.935	0.951	0.983
Brisbane, Australia	BNE	0.655	0.718	0.912
Guangzhou, China	CAN	0.651	0.665	0.979
Jakarta, Indonesia	CGK	0.854	0.867	0.985
Christchurch, New Zealand	CHC	0.357	0.371	0.964
Chiang Mai, Thailand	CNX	0.245	0.329	0.745
Haikou, China	HAK	0.366	0.421	0.870
Hat Yai, Thailand	HDY	0.134	0.208	0.645
Hong Kong, Hong Kong	HKG	1.000	1.000	1.000
Phuket, Thailand	HKT	0.393	0.528	0.743
Seoul, Korea	ICN	0.962	0.962	1.000
Osaka, Japan	KIX	0.743	1.000	0.743
Kuala Lumpur, Malaysia	KUL	0.652	0.657	0.992
Macau	MFM	0.465	0.844	0.555
Tokyo, Japan	NRT	0.860	0.876	0.982
Penang, Malaysia	PEN	0.386	0.898	0.430
Shanghai, China	PVG	0.909	0.931	0.976
Seoul, South Korea	SEL	0.618	0.619	0.999
Singapore, Singapore	SIN	0.927	0.934	0.993
Sydney, Australia	SYD	0.828	0.837	0.991
Shenzhen, China	SZX	0.721	0.949	0.760
Xiamen, China	XMN	1.000	1.000	1.000
Amsterdam, Netherlands	AMS	0.637	0.856	0.745
Stockholm, Sweden	ARN	0.410	0.453	0.905
Athens, Greece	ATH	0.464	0.471	0.987
Barcelona, Spain	BCN	0.731	0.763	0.959
Birmingham, England	BHX	0.365	0.367	0.994
Brussels, Belgium	BRU	0.370	0.419	0.881
Bratislava, Slovak	BTS	0.102	0.105	0.971
Budapest, Hungary	BUD	0.331	0.332	0.996
Paris, France	CDG	0.826	0.922	0.896
Cologne, Germany	CGN	0.299	0.388	0.771
Rome, Italy	CIA	0.488	0.612	0.797
Copenhagen, Denmark	CPH	0.369	0.385	0.960
Dublin, Ireland	DUB	0.457	0.468	0.976
Dusseldorf, Germany	DUS	0.324	0.341	0.951
Edinburgh, Scotland	EDI	0.693	0.799	0.868

Rome, Italy	FCO	0.517	0.585	0.885
Frankfurt, Germany	FRA	0.759	0.846	0.897
Geneva, Switzerland	GVA	0.418	0.443	0.953
Hamburg, Germany	HAM	0.384	0.386	0.993
Helsinki, Finland	HEL	0.326	0.409	0.796
Istanbul, Turkey	IST	0.611	0.716	0.853
London, England	LGW	0.995	1.000	0.995
London, England	LHR	0.998	0.999	0.999
Lisbon, Portugal	LIS	0.527	0.538	0.980
Ljubljana, Slovenia	LJU	0.198	0.207	0.958
Madrid, Spain	MAD	0.969	0.995	0.974
Manchester, England	MAN	0.488	0.498	0.981
Valleta, Malta	MLA	0.144	0.144	1.000
Munich, Germany	MUC	0.678	0.743	0.913
Paris, France	ORY	0.556	0.570	0.974
Oslo, Norway	OSL	0.526	0.539	0.975
Prague, Czech Republic	PRG	0.319	0.397	0.807
Riga, Latvia	RIX	0.206	0.227	0.909
Sofia, Bulgaria	SOF	0.186	0.205	0.910
London, England	STN	0.911	0.970	0.940
Tallinn, Estonia	TLL	0.163	0.180	0.902
Berlin, Germany	TXL	0.372	0.377	0.986
Vienna, Austria	VIE	0.507	0.508	0.997
Warsaw, Poland	WAW	0.349	0.355	0.986
Zurich, Switzerland	ZRH	0.434	0.497	0.874
Albuquerque, USA	ABQ	0.351	0.420	0.851
Albany, USA	ALB	0.195	0.243	0.827
Atlanta, USA	ATL	1.000	1.000	1.000
Austin, USA	AUS	0.381	0.453	0.867
Nashville, USA	BNA	0.344	0.362	0.958
Boston, USA	BOS	0.401	0.572	0.703
Baltimore, USA	BWI	0.402	0.484	0.835
Cleveland, USA	CLE	0.318	0.397	0.800
Charlotte, USA	CLT	0.793	0.835	0.949
Cincinnati, USA	CVG	0.550	0.626	0.877
Washington, USA	DCA	0.495	0.617	0.803
Denver, USA	DEN	0.599	0.898	0.667
Dallas, USA	DFW	0.596	0.840	0.711
Detroit, USA	DTW	0.419	0.572	0.736
Newark, USA	EWR	0.892	0.939	0.951
Ft. Lauderdale, USA	FLL	0.559	0.584	0.956
Honolulu, USA	HNL	0.458	0.653	0.702
Washington, USA	IAD	0.510	0.553	0.935

Houston, USA	IAH	0.575	0.702	0.814
Indianapolis, USA	IND	0.581	0.705	0.823
Jacksonville, USA	JAX	0.291	0.306	0.953
New York, USA	JFK	0.973	0.973	1.000
Las Vegas, USA	LAS	0.721	0.855	0.845
Los Angeles, USA	LAX	0.956	1.000	0.956
New York, USA	LGA	1.000	1.000	1.000
Kansas City, USA	MCI	0.255	0.298	0.855
Orlando, USA	MCO	0.574	0.651	0.881
Chicago, USA	MDW	0.690	0.697	0.990
Memphis, USA	MEM	0.996	0.999	0.998
Miami, USA	MIA	0.505	0.675	0.747
Milwaukee, USA	MKE	0.560	0.562	0.998
Minneapolis, USA	MSP	0.556	0.617	0.906
New Orleans, USA	MSY	0.245	0.247	0.993
Oakland, USA	OAK	0.839	0.849	0.988
Ontario, USA	ONT	0.442	0.464	0.956
Chicago, USA	ORD	0.768	1.000	0.768
West Palm Beach, USA	PBI	0.468	0.485	0.964
Portland, USA	PDX	0.457	0.520	0.881
Philadelphia, USA	PHL	0.510	0.678	0.751
Phoenix, USA	PHX	0.698	0.718	0.973
Pittsburgh, USA	PIT	0.262	0.437	0.606
Raleigh, USA	RDU	0.425	0.481	0.892
Richmond, USA	RIC	0.306	0.314	0.978
Reno, USA	RNO	0.257	0.299	0.886
San Diego, USA	SAN	0.826	1.000	0.826
San Antonio, USA	SAT	0.376	0.492	0.814
Louisville, USA	SDF	0.970	0.971	0.999
Seattle, USA	SEA	0.743	0.768	0.967
San Francisco, USA	SFO	0.585	0.677	0.865
San José, USA	SJC	0.433	0.459	0.945
Salt Lake City, USA	SLC	0.439	0.677	0.649
Sacramento, USA	SMF	0.402	0.441	0.912
Costa Mesa, USA	SNA	0.893	1.000	0.893
St. Louis, USA	STL	0.288	0.435	0.662
Tampa, USA	TPA	0.451	0.506	0.893
Edmonton, Canada	YEG	0.332	0.335	0.990
Halifax, Canada	YHZ	0.289	0.303	0.955
Ottawa, Canada	YOW	0.297	0.317	0.935
Montréal, Canada	YUL	0.311	0.418	0.743
Vancouver, Canada	YVR	0.510	0.634	0.804
Winnipeg, Canada	YWG	0.502	0.518	0.970

Calgary, Canada	YYC	0.732	0.745	0.983
Toronto, Canada	YYZ	0.371	0.484	0.765

Table A3: Average TE scores and scale efficiency by region (2005-2006 average)
Model with 3 Outputs (passengers, cargo and aircraft movements) and 2 Inputs (runways and employees)

World Region	Technical efficiency			Returns to scale diagnosis (% of observations)		
	CRS	VRS	Scale	IRS	CRS	DRS
Latin America	0.283	0.399	0.796	63.6	6.8	29.5
Asia	0.477	0.528	0.901	38.5	2.6	59.0
Europe	0.454	0.512	0.886	47.0	7.6	45.5
Canada & US	0.443	0.491	0.911	36.8	5.6	57.6
All	0.425	0.487	0.885	43.8	5.8	50.4

Table A4: LAC airports TFPC (Annual %)

Year	Argentina			Brazil						Chile	Colombia		Costa Rica
	AEP	EZE	FTE	BSB	CGH	GIG	GRU	MAO	VCP	SCL	BAQ	CLO	SJO
1995-1996	-	-	-	9.9	8.4	4.1	11.7	-21.5	-4.4	-	-	-	
1996-1997	-	-	-	23.6	20.3	9.3	5.3	-3.0	9.0	-	-	-	
1997-1998	-	-	-	9.6	17.7	8.8	0.2	15.2	8.5	-	-32.1	-	
1998-1999	-	-	-	-1.5	9.1	**-22.7**	-2.5	4.0	-8.4	-	-12.7	-	
1999-2000	-	-	-	8.2	12.9	5.6	1.2	5.9	20.0	11.8	9.2	-	
2000-2001	**-40.1**	-24.8	-	-1.5	13.1	-1.6	-5.7	-7.6	-1.7	**-9.7**	-27.8	-	
2001-2002	-15.8	-41.9	-	10.0	3.7	-8.2	-1.4	6.2	-22.7	-10.4	-0.9	-23.7	57.0
2002-2003	2.8	22.2	-	**-4.4**	-16.3	-16.5	2.3	-2.5	-20.0	3.7	-9.7	15.3	-5.0
2003-2004	5.9	20.0	60.3	12.1	**-84.2**	6.5	2.6	9.6	0.6	2.8	-2.8	-17.2	1.2
2004-2005	-2.5	-9.0	14.6	**-39.0**	9.0	43.7	9.4	2.0	-6.6	5.7	3.0	-5.2	-0.6
2005-2006	-9.3	5.2	3.9	-11.0	-15.4	2.3	-6.7	3.0	-18.6	-2.2	4.5	-2.6	-4.1
2006-2007	-5.5	1.9	19.7	9.2	**-26.5**	16.9	6.0	12.8	26.5	**-15.2**	1.3	5.9	3.6

Note: In bold are indicated the year of changes in capital stock, either in the number of runways or in the number of boarding bridges.

Table A4 (continued): LAC airports TFPC (Annual %)

Year	Ecuador	El Salvador	Mexico				Panama	Peru	Dom. Rep
	GYE	SAL	CUN	GDL	MEX	MTY	PTY	LIM	SDQ
1995-1996	-	-	-	-	-	-	-	-	-
1996-1997	-	-	-	-	-	-	-	-	-
1997-1998	-	-	-	-	-	-	-	-	-
1998-1999	-	-	-	-	-	-	-	-	-
1999-2000	-	-	18.5	-	0.8	-1.2	-	-	-
2000-2001	-	-	-3.3	-	**-9.9**	-5.9	-	-	-
2001-2002	-	7.4	1.9	-	0.4	18.0	-	-	-
2002-2003	-	-1.8	10.4	-6.1	2.2	14.1	-	-	-
2003-2004	-	12.4	10.2	5.1	6.0	1.7	9.0	-	-
2004-2005	-	-0.6	-8.2	**-13.9**	3.3	3.8	6.8	-	-9.1
2005-2006	**-28.2**	-0.9	-2.1	12.3	5.5	-0.5	**-20.3**	9.6	**-10.5**
2006-2007	8.1	-4.7	**-1.7**	11.3	**-6.9**	14.2	6.3	9.8	2.0

Note: In bold are indicated the year of changes in capital stock, either in the number of runways or in the number of boarding bridges.

Methodological Appendix

Data Envelopment Analysis (DEA)

DEA is a non-parametric method where the frontier surface is a sequence of interconnected hyper-planes that are constructed using linear programming methods. Technical efficiency scores are produced simultaneously as part of the LP optimisation process.

Assuming i =1, 2, …N units, **Y** a $M \times N$ output matrix and **X** a $K \times N$ matrix of inputs, the output-orientated variable returns to scale (VRS) DEA frontier is computed as the solution to N linear programs, for each unit i, of the form:

$$
\begin{aligned}
&\max_{\lambda} \theta, \\
&\text{st} \quad \mathbf{Y}\boldsymbol{\lambda} \geq \theta \mathbf{y}_i, \\
&\qquad \mathbf{X}\boldsymbol{\lambda} \leq \mathbf{x}_i, \\
&\qquad \mathbf{N1}'\boldsymbol{\lambda}=1, \\
&\quad \boldsymbol{\lambda} \geq \mathbf{0},
\end{aligned}
$$

where θ, $0 \leq \theta \leq 1$, indicates the potential radial expansion of the M outputs that could be achieved by the i-th unit, with input quantities held constant. Peers of unity i are identified by $\lambda > 0$ parameters. For further details, see Coelli *et al* (2005).

The output-orientated constant returns to scale (CRS) DEA model is used to calculate scale efficiency (as ratios of TE-VRS to TE-CRS efficiency scores). The CRS DEA is defined by the solution to N linear programs of the form:

$$
\begin{aligned}
&\max_{\lambda} \theta, \\
&\text{st} \quad \mathbf{Y}\boldsymbol{\lambda} \geq \theta \mathbf{y}_i, \\
&\qquad \mathbf{X}\boldsymbol{\lambda} \leq \mathbf{x}_i, \\
&\quad \boldsymbol{\lambda} \geq \mathbf{0},
\end{aligned} \qquad (9)
$$

which is equivalent to the VRS model with the convexity constraint ($\mathbf{N1}'\boldsymbol{\lambda}$=1) omitted.